

1

2       **Impact of sensor degradation on the MODIS NDVI time series**

3

4       Dongdong Wang <sup>a\*</sup>, Douglas Morton <sup>b</sup>, Jeffrey Masek <sup>b</sup>, Aisheng Wu <sup>c</sup>, Jyoteshwar Nagol <sup>a</sup>, Xiaoxiong  
5                   Xiong <sup>b</sup>, Robert Levy <sup>c</sup>, Eric Vermote <sup>a</sup>, Robert Wolfe <sup>b</sup>

6

7                   <sup>a</sup> Department of Geography, University of Maryland, College Park, MD 20742

8                   <sup>b</sup> NASA Goddard Space Flight Center, Greenbelt, MD 20771

9                   <sup>c</sup> Science Systems and Applications, Inc., 10210 Greenbelt Road, Lanham, MD 20706

10

11                   \*Author for Correspondence:

12                   Dongdong Wang

13                   Department of Geography, University of Maryland,

14                   2181 LeFrak Hall, College Park, MD 20742, USA.

15                   Fax: +1-301-314-9299, Phone: +1-301-405-4538, Email: ddwang@umd.edu

16

17                   Submitted to Geophysical Research Letters

18

19    **Abstract**

20    Time series of satellite data provide unparalleled information on the response of vegetation to  
21    climate variability. Detecting subtle changes in vegetation over time requires consistent  
22    satellite-based measurements. Here, we evaluated the impact of sensor degradation on trend  
23    detection using Collection 5 data from the Moderate Resolution Imaging Spectroradiometer  
24    (MODIS) sensors on the Terra and Aqua platforms. For Terra MODIS, the impact of blue band  
25    (Band 3, 470nm) degradation on simulated surface reflectance was most pronounced at near-  
26    nadir view angles, leading to a  $0.001\text{-}0.004 \text{ yr}^{-1}$  decline in Normalized Difference Vegetation  
27    Index (NDVI) under a range of simulated aerosol conditions and surface types. Observed trends  
28    MODIS NDVI over North America were consistent with simulated results, with nearly a  
29    threefold difference in negative NDVI trends derived from Terra (17.4%) and Aqua (6.7%)  
30    MODIS sensors during 2002-2010. Planned adjustments to Terra MODIS calibration for  
31    Collection 6 data reprocessing will largely eliminate this negative bias in NDVI trends over  
32    vegetation.

33    **1. Introduction**

34    Satellite data capture changes in the land surface, atmosphere, and ocean on diurnal to decadal  
35    time scales. Large and remote areas can be monitored using satellite data, and at nearly 40  
36    years, the lengthening time series of satellite observations offers insight into climate impacts on  
37    human and natural systems. In particular, satellite-based studies of changes in vegetation  
38    phenology from seasonal, annual, and decadal-scale temperature variability have received  
39    considerable attention in recent years (e.g., [Myneni *et al.*, 1997], [Goetz *et al.*, 2005], [Wang *et*

40     *al.*, 2011]). Detecting subtle changes in vegetation characteristics requires long time series of  
41     data from well-calibrated sensors [Slayback *et al.*, 2003] and careful attention to uncertainties  
42     associated with atmospheric correction [Nagol *et al.*, 2009] and sensor degradation.

43     Data from the Moderate Resolution Imaging Spectroradiometer (MODIS) sensors on board the  
44     NASA Terra (2000-present) and Aqua (2002-present) satellites provide a unique opportunity to  
45     assess the consistency of satellite-based measurements. Data products from both sensors are  
46     generated using consistent algorithms, and MODIS standard products support a range of  
47     science applications (e.g. [Esaias *et al.*, 1998; Justice *et al.*, 2002; King *et al.*, 2003]). Recently,  
48     several studies have reported inconsistent results from the Terra and Aqua MODIS sensors,  
49     including estimates of ocean chlorophyll-a concentrations [Djavidnia *et al.*, 2010] and aerosols  
50     [Levy *et al.*, 2010]. Such discrepancies may impact the interpretation of time series or even the  
51     ability to detect time-dependent trends, especially for MODIS products that utilize data from  
52     both Terra and Aqua MODIS sensors.

53     Here, we analyzed the impact of sensor degradation on trends in MODIS normalized difference  
54     vegetation index (NDVI) over boreal forest and tundra cover types in North America, biomes  
55     previously identified as undergoing rapid climate-driven changes in productivity [de Jong *et al.*,  
56     2011; Pouliot *et al.*, 2009]. We calculated degradation coefficients for each MODIS spectral  
57     band, and we propagated the time-varying trends in MODIS degradation through a simplified  
58     version of the MODIS atmospheric correction process. We then compared the simulated NDVI  
59     trends to observed trends in NDVI from the Terra and Aqua MODIS sensors over boreal North  
60     America. Our study indicates that negative NDVI trends of up to  $-0.004 \text{ yr}^{-1}$  can be attributed

61 solely to degradation of the visible and near-infrared (NIR) bands aboard the Terra MODIS  
62 instrument. We demonstrate the need to consider sensor calibration issues when interpreting  
63 decadal scale trends in land, ocean, and atmospheric constituents.

64 **2. Data and methods**

65 **2.1 MODIS Top-of-Atmosphere reflectance**

66 Sensor degradation is a common occurrence as satellite instruments age in the harsh space  
67 environment. In theory, sensor calibration using onboard apparatus can correct for sensor  
68 degradation, but in practice, the solar diffuser, stimulation lamps, and stability monitors  
69 needed for onboard calibration also change during mission life. A useful secondary source of  
70 information is to monitor reflectance trends with “pseudo-invariant” desert targets, which  
71 appear to be radiometrically and spectrally stable during the satellite era [Cosnefroy et al.,  
72 1996].

73 We used MODIS C5 top-of-atmosphere (TOA) reflectance data collected over the Libya 4 desert  
74 site (28.44N, 23.39E) to estimate degradation of the Terra (2000-2010) and Aqua (2002-2010)  
75 MODIS sensors over time. Level 1b TOA data for MODIS Bands 1 (red), 2 (NIR), and 3 (blue)  
76 were extracted from 16-day repeatable orbits over the site to maintain consistent sensor  
77 viewing angles. TOA reflectances were normalized using site-specific bi-directional reflectance  
78 function (BRDF) coefficients determined from the first three years of Terra and Aqua  
79 observations [Wu et al., 2008]. The BRDF normalized TOA data time series for each view angle

80 (frame), spectral band, and mirror side were fitted using a second-order polynomial to estimate  
81 degradation for days since launch (DSL):

82 
$$Degradation = C_0 + C_1 \cdot DSL + C_2 \cdot DSL^2 \quad (1)$$

83 To estimate the impact of planned changes in sensor calibration for Collection 6 (C6) MODIS  
84 reprocessing (scheduled for late 2011), we adjusted the C5 degradation coefficients using the  
85 ratio of C5:C6 TOA reflectance for the Libya 4 site (Figure S1). Prototype C6 TOA data were  
86 generated over selected targets to evaluate the impact of calibration changes on MODIS data  
87 products. C6 data for the entire MODIS time series will not be available until at least 2012.  
88 Therefore, we also estimated the potential for continued degradation in C5 Terra data by  
89 extending the fitted degradation curves to 2013 (Figure S2).

90 **2.2 Simulation of atmospheric radiative transfer and atmospheric correction**

91 We used the time-dependent degradation coefficients for C5 Terra MODIS data to simulate the  
92 impact of sensor degradation on trends in NDVI over boreal North America during 2000-2010.  
93 The simulation included three major steps. First, we generated 11-year time series of TOA  
94 reflectance for forest and tundra cover types under a range of aerosol conditions, adjusting  
95 TOA values for sensor degradation over time. Our simulation approach was similar to the  
96 methods used to generate the MODIS surface reflectance product (MOD09, [Vermote et al.,  
97 2002][Vermote and Kotchenova, 2008]), with several simplifying assumptions. We used the 6S  
98 vector atmospheric radiative transfer model (Version 1.1, [Kotchenova et al., 2006]). To  
99 improve computational efficiency, we built look-up tables (LUTs) of spherical albedo ( $\rho$ ), path

100 reflectance ( $r_0$ ), and transmittance ( $\gamma$ ). These LUTs were based on 15 aerosol optical depth  
101 (AOD) values (0.01 - 2.0), three aerosol models (continental, background desert, and biomass  
102 burning), and small angular intervals (5 degree steps for solar and view zenith angles and 10  
103 degree steps for relative azimuth angle). These three LUTs were used to relate TOA reflectance  
104 (r) and surface reflectance ( $r_s$ ) [Liang, 2004]:

105

$$r = r_0 + \frac{r_s}{1 - r_s \rho} \gamma \quad (2)$$

106 Mid-summer surface reflectance inputs for different cover types were derived from Aqua  
107 MODIS NDVI data (MYD13C1, [Huete et al., 2002]). NDVI values were binned in increments of  
108 0.1, and mean spectral reflectance values were estimated for each NDVI bin. Using equation 2,  
109 we then estimated TOA reflectance for each NDVI bin under different aerosol conditions using  
110 the LUTs described above. Finally, TOA reflectance values for each year were multiplied by the  
111 degradation coefficients estimated for C5 Terra MODIS data to simulate the TOA reflectance  
112 observed by the sensor for each view zenith angle (VZA) and spectral band.

113 In the second step, simulated Terra MODIS surface reflectance values were derived from the  
114 degraded TOA reflectance values. We used a simplified Dense Dark Vegetation algorithm  
115 [Kaufman et al., 1997] to retrieve AOD. Our two simplifications were 1) direct use of Band 3  
116 surface reflectance, rather than estimating Band 3 reflectance using other MODIS bands  
117 [Kaufman et al., 1997], since C5 Terra MODIS degradation impacts were minimal for longer  
118 wavelengths, and 2) a single estimate of AOD at 550 nm from Band 3, thereby ignoring the

119 spectrum dependence of AOD, because the aerosol model was known in our simulations.

120 Given AOD, we can solve equation (2) for surface reflectance:

121

$$r_s = \frac{r - r_0}{\gamma + (r - r_0)\rho} \quad (3)$$

122 Finally, time series of NDVI values were calculated using the estimated red and NIR surface

123 reflectance values [Huete *et al.*, 2002] for each NDVI bin, year, and set of atmospheric

124 conditions (AOD and aerosol model).

125 **2.3 Monte Carlo simulation**

126 While the radiative transfer modeling allowed us to estimate the effect of sensor degradation

127 on an individual NDVI time series, it did not address the issue of how such degradation might

128 confound the extraction of vegetation trends from a large (e.g. continental) set of data. In

129 particular, we wished to understand whether the degradation-induced errors were significant

130 compared to the stated uncertainty (random error) of the NDVI product. To explore this issue,

131 we used a set of Monte Carlo simulations to examine the sensitivity of NDVI time series trend

132 detection to artifacts from sensor degradation. Annual time series of NDVI from 2000-2010

133 were used as inputs to the Monte Carlo simulation. Each time series had an “actual” linear

134 NDVI trend of varying magnitude ( $-0.02 \text{ yr}^{-1}$  to  $+0.02 \text{ yr}^{-1}$ ), as well as normally-distributed

135 random errors applied to the NDVI values. The standard deviation of the random error

136 distribution was set 0.015, based on MODIS validation studies over AERONET sun photometer

137 sites (<http://modis-sr.ltdri.org/>). The NDVI time series with random noise were fit with a linear

138 trend, using a t-test and 95% confidence interval to identify statistically significant linear trends.

139 Three variables were calculated for each set of Monte Carlo simulations. The bias in trend  
140 detection was estimated using the mean of all statistically significant trends,  $\mu(T_{Detected})$ , and  
141 the actual trend,  $T_0$ :

142

$$Bias = \frac{\mu(T_{Detected}) - T_0}{T_0} \quad (4)$$

143 The rate of missing detections was estimated as the fraction of all time series (N) in which  
144 statistically significant trends did not have the correct positive or negative signs ( $n_{correct}$ ):

145

$$Missing = 1 - \frac{n_{correct}}{N} \quad (5)$$

146 The rate of false detections was estimated as the fraction of all statistically significant trends  
147 ( $n_{sig}$ ) in which statistically significant trends had the opposite signs ( $n_{incorrect}$ ):

148

$$False = \frac{n_{incorrect}}{n_{sig}} \quad (6)$$

149 **2.4 MODIS NDVI trends for North America**

150 For comparison with the simulated impacts of sensor degradation described above, we mapped  
151 trends in Terra and Aqua MODIS NDVI for boreal North America during 2002-2010. We  
152 analyzed high quality NDVI values from the C5 MODIS 500m vegetation indices product  
153 (MOD13A1/MYD13A1, [Huete et al., 2002]). Data were selected for four 16-day composites  
154 during the growing season (starting on day of year 177, 193, 209, and 225) to minimize impacts  
155 of vegetation phenology, and time series analyses were conducted separately for each

156 compositing period. Only pixels with high-quality NDVI observations in at least 6 out of the 9-  
157 year record were included in the analysis. NDVI time series were fit with a linear trend, using a  
158 t-test and 95% confidence interval to identify statistically significant linear trends. For pixels  
159 with statistically significant NDVI trends in more than one compositing period, only pixels in  
160 which all statistically significant trends had the same slope direction (positive or negative) were  
161 retained for the final map. A map of forest disturbances between 1990-2000 was used to  
162 exclude areas of fire damage or timber harvest predating the MODIS record [Masek et al., 2008],  
163 and likely disturbance areas during the MODIS era were excluded using a threshold of NDVI  
164 change between sequential observations (>0.2).

165 **3. Results**

166 Sensor degradation varied by spectral band, view angle, and mirror side (Figure 1, S3). Overall,  
167 Aqua MODIS Bands 1-3 showed <2% change in TOA reflectance between 2002-2010, while  
168 Terra MODIS data exhibited substantial degradation, particularly at shorter wavelengths (Figure  
169 1, S3). Terra MODIS Band 3 had the most pronounced degradation, with a decrease of nearly  
170 7% at near-nadir view angles over the past decade (Figure 1). Band 3 is not used directly for  
171 calculating NDVI; instead, degradation of Band 3 TOA reflectance over time will impact the  
172 calculation of surface reflectance in other spectral bands [Kotchenova et al., 2008; Vermote et  
173 al., 2002] and higher-level MODIS products, including NDVI.

174 Degradation of the Terra MODIS blue band resulted in decreasing NDVI trends (2000-2010) for  
175 simulated tundra and forest cover types under a range of aerosol conditions (Figure 2).  
176 Changes in NDVI arose from the decreasing trend in retrieved AOD from degraded blue TOA

177 reflectance. Three aerosol models were tested, yet the choice of aerosol model had little  
178 impact on retrieved AOD values in our simulations. For a moderate (AOD = 0.2) and high (AOD =  
179 0.5) aerosol loading, retrieved AOD declined by approximately 0.1 between 2000 and 2010.  
180 Under the low aerosol case, retrieved AOD reached the minimum simulation value (0.01) as the  
181 blue reflectance decreased over time.

182 Negative trends in NDVI varied by VZA and aerosol loading (Table 1, S1). For moderate AOD,  
183 NDVI over forest and tundra declined by  $0.003 \text{ yr}^{-1}$  at near-nadir VZA but  $\leq 0.001 \text{ yr}^{-1}$  for VZA  
184  $\geq 30^\circ$  from nadir. Simulations with high AOD had even stronger NDVI declines from sensor  
185 degradation ( $> 0.004 \text{ yr}^{-1}$ , Table S1). In general, rates of declining NDVI were similar for tundra  
186 and forest types when comparing simulations with the same AOD and VZA (Figure 2, S4). Low  
187 and high scenarios bounded the likely impacts of sensor degradation on time-varying trends in  
188 Terra MODIS C5 NDVI of  $-0.001 \sim -0.004 \text{ yr}^{-1}$  (see Supplemental Materials and Tables S2, S3).

189 Implementing calibration changes planned for C6 MODIS reprocessing largely eliminated trends  
190 in Terra MODIS C5 NDVI from sensor degradation over 2000-2010. For moderate AOD over  
191 tundra, a limited number of off-nadir view angles retained small positive NDVI trends ( $0.001 \text{ yr}^{-1}$ )  
192 in simulations using C6 calibration information (Table S4).

193 The systematic NDVI decrease from Terra MODIS sensor degradation could bias trend detection  
194 using C5 data. Based on the Monte Carlo simulations, the bias in trend detection could  
195 be  $> 500\%$  when the actual NDVI change is small ( $< 0.002 \text{ yr}^{-1}$ ) and the degradation rate is large ( $-$   
196  $0.003 \text{ yr}^{-1}$ ). In this case, nearly all detected trends originated from sensor degradation rather  
197 than actual vegetation dynamics (Figure 3). When degradation of NDVI was simulated at  $-0.003$

198  $\text{yr}^{-1}$ , almost half of simulated NDVI trends of  $+0.006 \text{ yr}^{-1}$  could not be detected or were detected  
199 with the opposite sign. Even a degradation-based NDVI decline of  $-0.001 \text{ yr}^{-1}$  resulted in >50%  
200 missing detections of all NDVI trends between  $-0.002$  and  $+0.004 \text{ yr}^{-1}$ . Overall, the Monte Carlo  
201 simulations demonstrate that the combined impact of sensor degradation and product  
202 uncertainties have a large impact on correct identification of trends in MODIS NDVI.

203 The magnitude of simulated Terra NDVI decreases matched the observed distribution of  
204 positive and negative trends from Terra and Aqua MODIS data over North America. Both Terra  
205 and Aqua MODIS indicated regions with statistically significant negative (browning) and positive  
206 (greening) NDVI trends during 2002-2010 (Figure 4). However, there was a threefold difference  
207 in the area of negative NDVI trends from Terra compared to Aqua, with large contiguous  
208 regions where Terra data indicated small negative NDVI trends. NDVI trends over boreal forest  
209 and tundra vegetation were small, with the mode of Aqua NDVI trend of  $+0.008 \text{ year}^{-1}$ . Monte  
210 Carlo simulations (Section 3.2) suggest that these subtle changes fall within the range of time  
211 series trends that may be impacted by the combination of sensor degradation and product  
212 uncertainties. The combination of subtle changes in NDVI and comparable impacts from sensor  
213 degradation resulted in substantial differences in the spatial patterns of NDVI trends from Terra  
214 and Aqua. For the pixels with statistically significant trends in both maps, the mean difference  
215 between Terra and Aqua NDVI trends was  $-0.002 \text{ yr}^{-1}$  (Figure S5), similar to the simulated  
216 decline in Terra MODIS NDVI from sensor degradation.

217 **4. Discussion & Conclusions**

218 Based on our simulations, we expect degradation of the Terra MODIS blue band to result in  
219 negative NDVI trends over tundra and boreal forest vegetation, with greater impacts at the  
220 near-nadir VZAs favored in the MODIS reflectance and NDVI products. Previous studies based  
221 on AVHRR and Landsat data have identified greening and browning trends of 0.005-0.01 NDVI  
222  $\text{yr}^{-1}$  in the boreal and tundra regions of North America [*de Jong et al.*, 2011; *Pouliot et al.*, 2009].  
223 Our simulations suggest that up to half of all actual NDVI trends of this magnitude could be  
224 missed by Terra MODIS when both sensor degradation and product uncertainties are  
225 considered. Initial simulations using data processed with prototype C6 algorithms indicate no  
226 significant trends associated with sensor degradation for near-nadir VZAs. Thus, it is expected  
227 that C6 will largely fix the issues described in this paper. Until C6 data are available for the  
228 Terra MODIS time series, we suggest that users rely on Aqua MODIS data for studies of inter-  
229 annual variability in NDVI.

230 Studies of subtle trends in vegetation cover may be particularly sensitive to artifacts from Terra  
231 MODIS sensor degradation. Many land products select near-nadir observations where sensor  
232 degradation was most pronounced, and the small negative bias in Terra MODIS NDVI from  
233 sensor degradation may be more easily confused with real browning trends over vegetation  
234 than cloud contamination or other sensor artifacts. Many other applications will be less  
235 sensitive to artifacts from sensor degradation, such as studies that use longer wavelengths or  
236 applications based on large and persistent changes in surface reflectance associated with land  
237 cover change.

238 Terra MODIS blue band degradation may also account for observed discrepancies in AOD from  
239 Terra and Aqua MODIS sensors. Levy et al. [2010] noted that Terra's AOD record showed a  
240 negative trend compared to ground-based AERONET sunphotometers while comparisons  
241 between AERONET and Aqua AOD showed no trend. Over land, MODIS aerosol retrieval is  
242 based on three bands, including Band 3 [Remer et al., 2005]. Sensitivity tests suggest that  $\geq 3\%$   
243 degradation of Band 3 is sufficient to explain the trend in Terra MODIS versus AERONET  
244 comparison. As with studies of vegetation, C5 Aqua MODIS data should be used for studies of  
245 inter-annual variability in aerosols until Band 3 degradation can be addressed in C6  
246 reprocessing.

247 Sensor calibration is critical for time series analyses. Long time series desired by the science  
248 community necessitate consistent calibration throughout the entire mission lifetime. In the  
249 case of MODIS, calibration efforts now utilize onboard equipment, monthly lunar observations,  
250 and pseudo-invariant ground targets to determine time-dependent and wavelength-dependent  
251 changes in the reflective solar bands. Instrument characteristics and on-orbit malfunctions also  
252 complicate sensor calibration. The observed degradation on Terra MODIS is thought to be  
253 associated with on-orbit changes in the bi-directional reflectance characteristics of the solar  
254 diffuser from those obtained in pre-launch tests, which is used along with measurements by the  
255 solar diffuser stability monitor to derive on-orbit degradation rates. Following an anomaly with  
256 the Terra MODIS solar diffuser in 2003, the solar diffuser door was fixed in the "open" position  
257 to keep the instrument screen permanently in place. Since that change, the rate of Terra MODIS  
258 degradation has increased. These issues highlight the importance of having multiple lines of

259 evidence for assessing sensor calibration, including the use of both on-board mechanisms and  
260 invariant ground targets.

261 Terra MODIS C5 data remain an important source of information for a range of science  
262 applications. However, time series analysis of vegetation or aerosol properties based directly  
263 or indirectly on C5 Terra MODIS Band 3 data may be sensitive to impacts of sensor degradation.  
264 Errors from sensor degradation remain within the uncertainties of the retrieval algorithm and  
265 instrument characteristics [*Vermote and Kotchenova, 2008*]. However, even small trends in  
266 sensor performance may influence time series analysis. C6 data reprocessing will likely alleviate  
267 the problems identified in this study, yet MODIS data users should consider the potential for  
268 sensor degradation to impact their analysis, given that the aging MODIS sensors will remain  
269 vulnerable to similar problems in the future.

270 **References:**

271 Cosnefroy, H. N., M. Leroy, and X. Briottet (1996), Selection and characterization of Saharan and Arabian  
272 desert sites for the calibration of optical satellite sensors, *Remote Sensing of Environment*, 58(1), 101-  
273 114.

274 de Jong, R., S. de Bruin, A. de Wit, M. E. Schaepman, and D. L. Dent (2011), Analysis of monotonic  
275 greening and browning trends from global NDVI time-series, *Remote Sensing of Environment*, 115(2),  
276 692-702.

277 Djavidnia, S., F. Melin, and N. Hoepffner (2010), Comparison of global ocean colour data records, *Ocean  
278 Science*, 6(1), 61-76.

279 Esaias, W. E., et al. (1998), An overview of MODIS capabilities for ocean science observations, *Ieee  
280 Transactions on Geoscience and Remote Sensing*, 36(4), 1250-1265.

281 Goetz, S. J., A. G. Bunn, G. J. Fiske, and R. A. Houghton (2005), Satellite-observed photosynthetic trends  
282 across boreal North America associated with climate and fire disturbance, *Proceedings of the National  
283 Academy of Sciences of the United States of America*, 102(38), 13521-13525.

284 Huete, A., K. Didan, T. Miura, E. P. Rodriguez, X. Gao, and L. G. Ferreira (2002), Overview of the  
285 radiometric and biophysical performance of the MODIS vegetation indices, *Remote Sensing of*  
286 *Environment*, 83(1-2), 195-213.

287 Justice, C. O., J. R. G. Townshend, E. F. Vermote, E. Masuoka, R. E. Wolfe, N. Saleous, D. P. Roy, and J. T.  
288 Morisette (2002), An overview of MODIS Land data processing and product status, *Remote Sensing of*  
289 *Environment*, 83(1-2), 3-15.

290 Kaufman, Y. J., D. Tanre, L. A. Remer, E. F. Vermote, A. Chu, and B. N. Holben (1997), Operational remote  
291 sensing of tropospheric aerosol over land from EOS moderate resolution imaging spectroradiometer,  
292 *Journal of Geophysical Research-Atmospheres*, 102(D14), 17051-17067.

293 King, M. D., W. P. Menzel, Y. J. Kaufman, D. Tanre, B. C. Gao, S. Platnick, S. A. Ackerman, L. A. Remer, R.  
294 Pincus, and P. A. Hubanks (2003), Cloud and aerosol properties, precipitable water, and profiles of  
295 temperature and water vapor from MODIS, *IEEE Transactions on Geoscience and Remote Sensing*, 41(2),  
296 442-458.

297 Kotchenova, S. Y., E. F. Vermote, R. Matarrese, and F. J. Klemm (2006), Validation of a vector version of  
298 the 6S radiative transfer code for atmospheric correction of satellite data. Part I: Path radiance, *Applied*  
299 *Optics*, 45(26), 6762-6774.

300 Kotchenova, S. Y., E. F. Vermote, R. Levy, and A. Lyapustin (2008), Radiative transfer codes for  
301 atmospheric correction and aerosol retrieval: intercomparison study, *Applied Optics*, 47(13), 2215-2226.

302 Levy, R. C., L. A. Remer, R. G. Kleidman, S. Mattoo, C. Ichoku, R. Kahn, and T. F. Eck (2010), Global  
303 evaluation of the Collection 5 MODIS dark-target aerosol products over land, *Atmospheric Chemistry*  
304 and Physics, 10(21), 10399-10420.

305 Liang, S. L. (2004), Quantitative remote sensing of land surfaces, John Wiley & Sons, Inc, Hoboken, New  
306 Jersey.

307 Masek, J. G., C. Q. Huang, R. Wolfe, W. Cohen, F. Hall, J. Kutler, and P. Nelson (2008), North American  
308 forest disturbance mapped from a decadal Landsat record, *Remote Sensing of Environment*, 112(6),  
309 2914-2926.

310 Myneni, R. B., C. D. Keeling, C. J. Tucker, G. Asrar, and R. R. Nemani (1997), Increased plant growth in the  
311 northern high latitudes from 1981 to 1991, *Nature*, 386(6626), 698-702.

312 Nagol, J. R., E. F. Vermote, and S. D. Prince (2009), Effects of atmospheric variation on AVHRR NDVI data,  
313 *Remote Sensing of Environment*, 113(2), 392-397.

314 Pouliot, D., R. Latifovic, and I. Olthof (2009), Trends in vegetation NDVI from 1km AVHRR data over  
315 Canada for the period 1985-2006, *International Journal of Remote Sensing*, 30(1), 149-168.

316 Remer, L. A., et al. (2005), The MODIS aerosol algorithm, products, and validation, *Journal of the*  
317 *Atmospheric Sciences*, 62(4), 947-973.

318 Slayback, D. A., J. E. Pinzon, S. O. Los, and C. J. Tucker (2003), Northern hemisphere photosynthetic  
 319 trends 1982-99, *Global Change Biology*, 9(1), 1-15.

320 Vermote, E. F., and S. Kotchenova (2008), Atmospheric correction for the monitoring of land surfaces,  
 321 *Journal of Geophysical Research-Atmospheres*, 113(D23).

322 Vermote, E. F., N. Z. El Saleous, and C. O. Justice (2002), Atmospheric correction of MODIS data in the  
 323 visible to middle infrared: first results, *Remote Sensing of Environment*, 83(1-2), 97-111.

324 Wang, X. H., S. L. Piao, P. Ciais, J. S. Li, P. Friedlingstein, C. Koven, and A. P. Chen (2011), Spring  
 325 temperature change and its implication in the change of vegetation growth in North America from 1982  
 326 to 2006, *Proceedings of the National Academy of Sciences of the United States of America*, 108(4), 1240-  
 327 1245.

328 Wu, A., A. Angal, X. Xiong, and C. Cao (2008), Monitoring MODIS calibration stability of visible and near-  
 329 IR bands from observed top-of-atmosphere BRDF-normalized reflectances over Libyan Desert and  
 330 Antarctic surfaces, *Proc. SPIE* 7081, 708113.

331

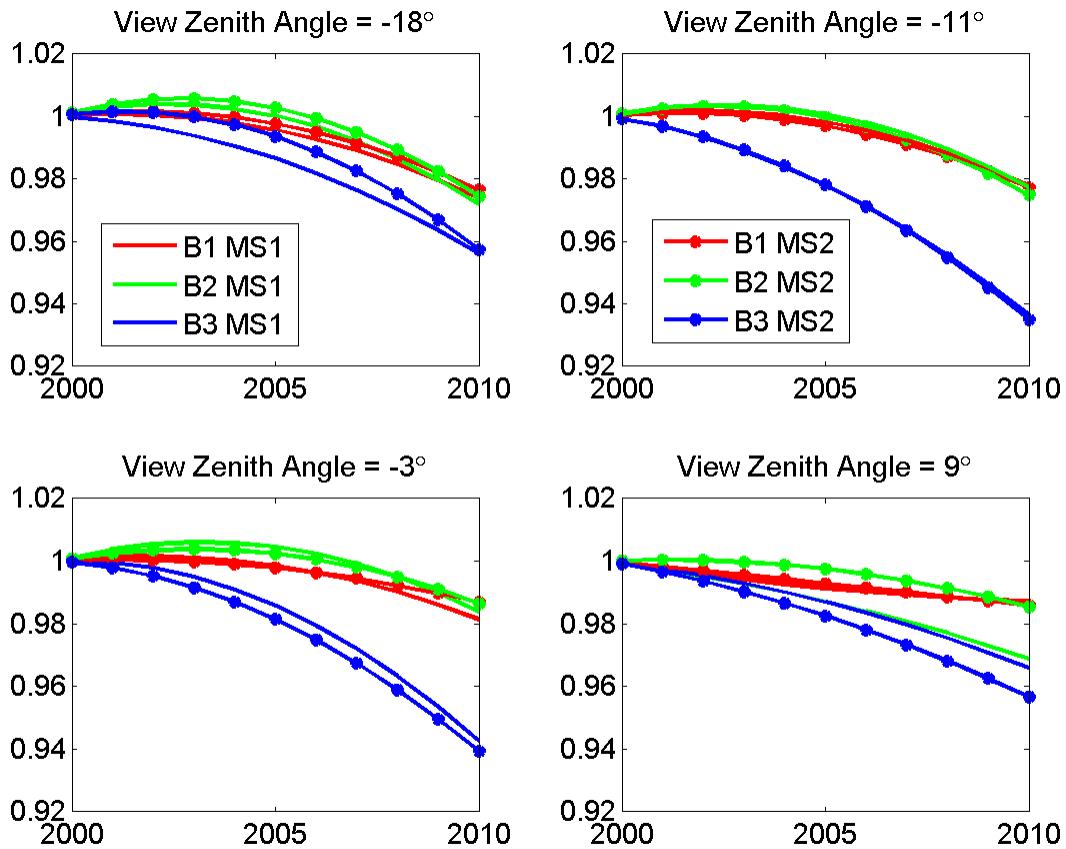
332 **Tables and figures**

333 Table 1. Annual trends in simulated Terra MODIS C5 NDVI during 2000-2010 over tundra (NDVI = 0.65)  
 334 based on moderate aerosol loading (AOD = 0.2). Results were calculated separately for each view zenith  
 335 angle (VZA) and mirror side (MS) using three different aerosol models. Negative VZAs refer to pixels  
 336 from the beginning of a scan line to nadir; positive VZAs indicate pixels from nadir to the end of a scan  
 337 line.

View Zenith Angle	-51	-42	-32	-28	-18	-11	-3	9	17	31	43	52	
MS1	Continental	*	-0.0008	-0.0008	-0.0012	-0.0023	-0.0031	-0.0027	-0.0023	-0.0011	-0.0010	0.0023	0.0034
	Desert	*	-0.0008	-0.0008	-0.0012	-0.0023	-0.0031	-0.0027	-0.0023	-0.0011	-0.0010	0.0023	0.0034
	Bio Burning	*	-0.0006	-0.0007	-0.0010	-0.0019	-0.0028	-0.0024	-0.0021	-0.0009	-0.0008	0.0022	0.0032
MS2	Continental	0.0003	*	-0.0007	-0.0019	-0.0023	-0.0033	-0.0030	-0.0022	-0.0016	-0.0013	0.0031	0.0053
	Desert	0.0003	*	-0.0007	-0.0018	-0.0023	-0.0033	-0.0031	-0.0022	-0.0016	-0.0013	0.0031	0.0053
	Bio Burning	0.0003	*	-0.0005	-0.0016	-0.0020	-0.0029	-0.0027	-0.0019	-0.0014	-0.0011	0.0028	0.0048

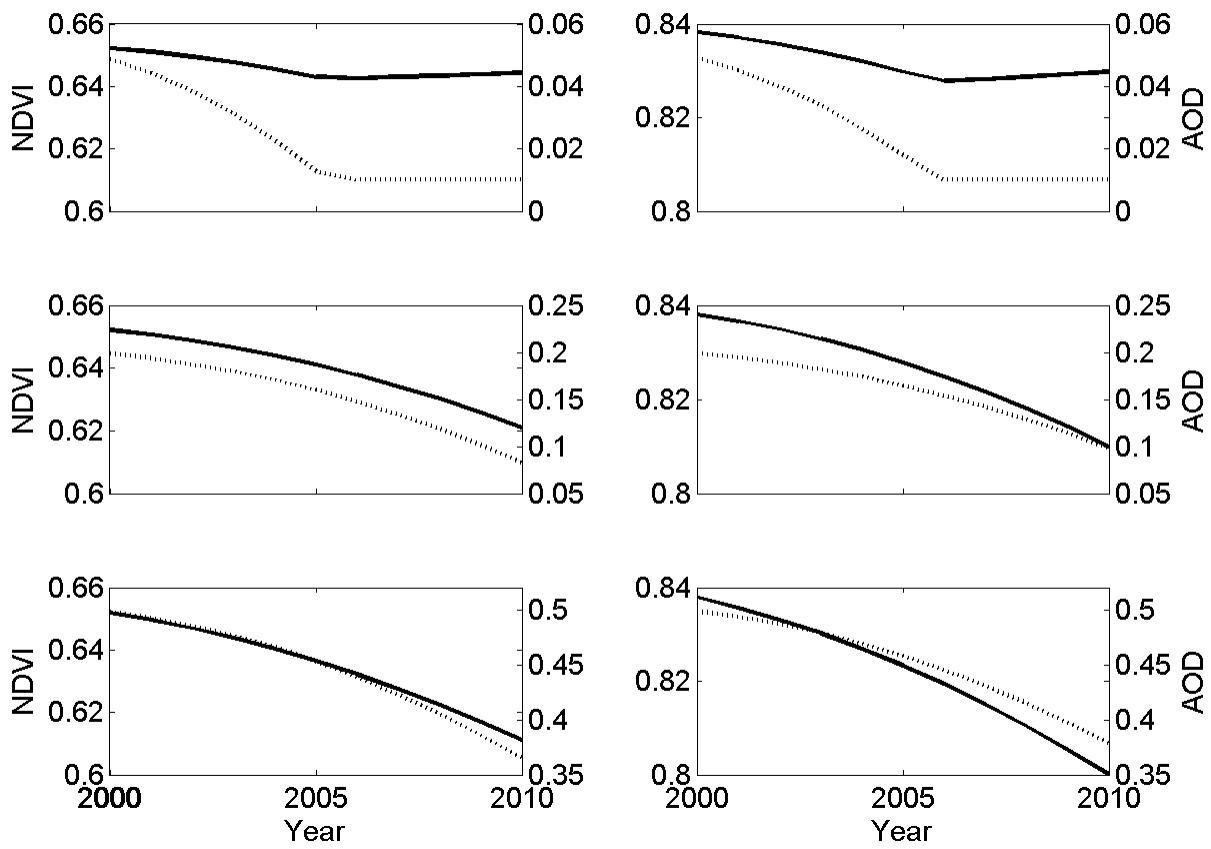
338 \* no significant trend detected

339



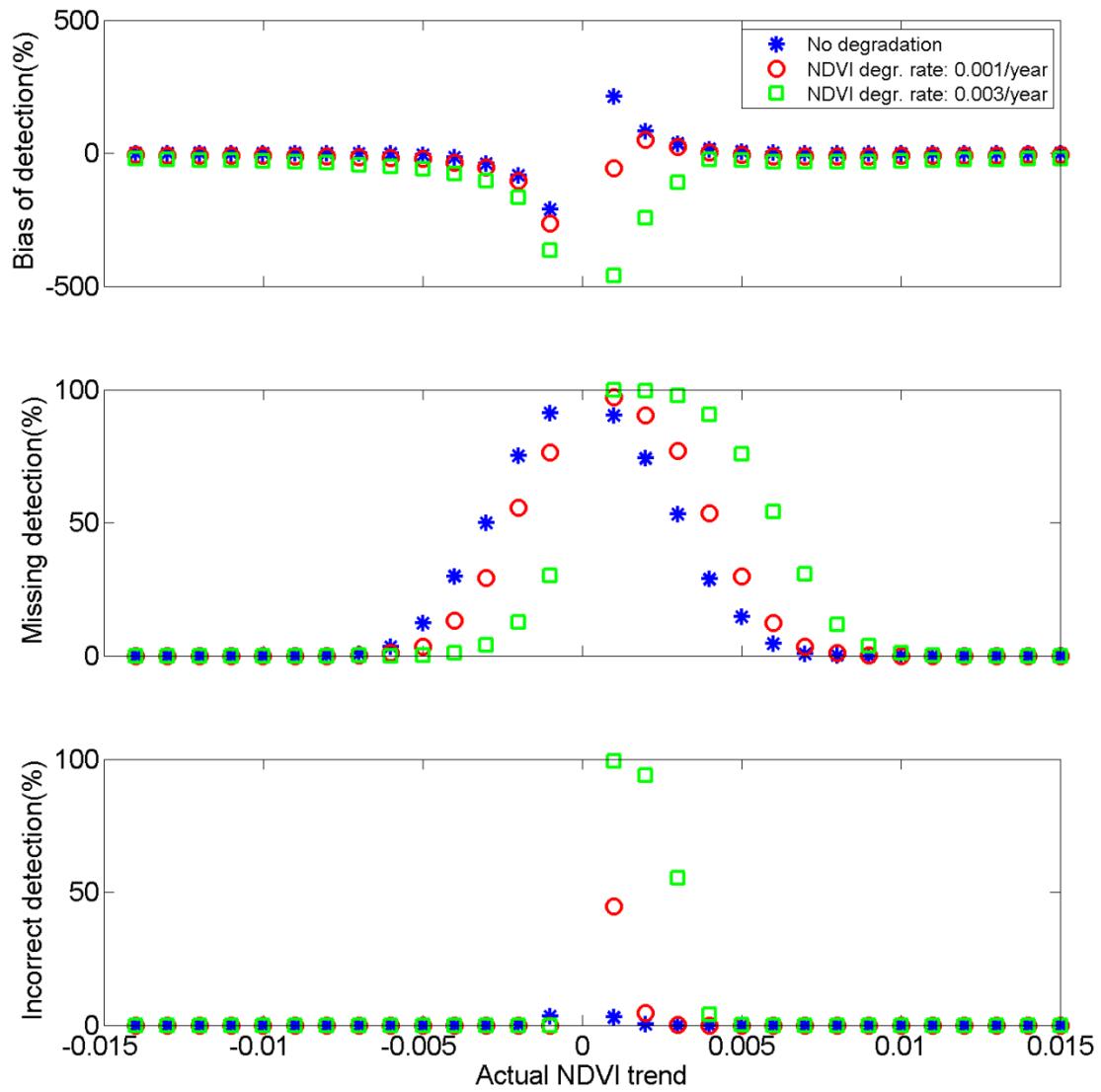
340

341 Figure 1. Fitted degradation coefficients for Terra MODIS C5 red (B1), NIR (B2), and blue (B3) top-of-  
 342 atmosphere reflectance using equation 1. Degradation coefficients were calculated separately for data  
 343 from Mirror Side 1 (MS1) and Mirror Side 2 (MS2). Additional VZAs are shown in Figure S1.



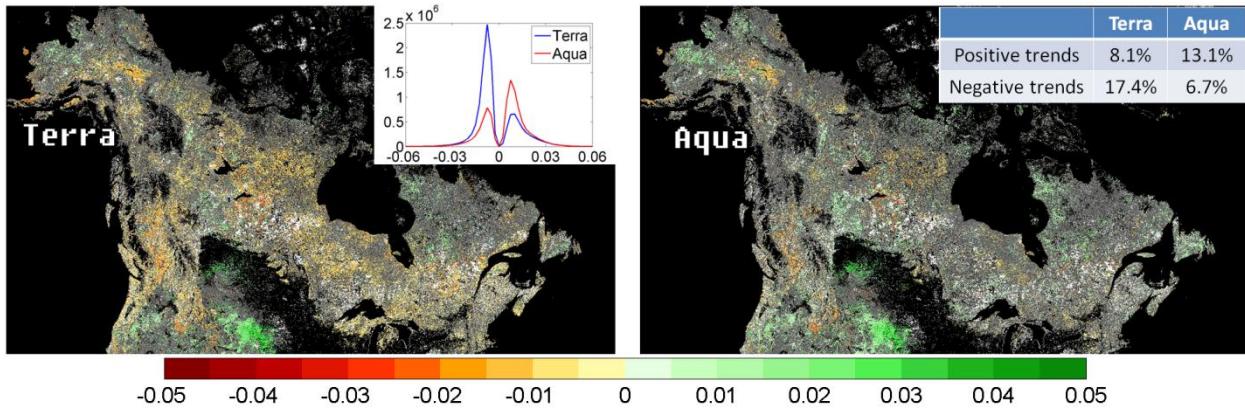
344

345 Figure 2. Simulated Terra MODIS C5 NDVI (solid lines) and AOD (dashed lines) time series for near-nadir  
 346 observations ( $VZA=11$ ) of tundra (left) and forest (right) during 2000-2010 with low (0.05, top),  
 347 moderate (0.2, middle), and high (0.5, bottom) AOD. Simulated NDVI and AOD time series for all VZAs  
 348 are shown in Figure S4.



349

350 Figure 3. Monte Carlo simulation results for the combined impacts of NDVI  
 351 degradation and NDVI uncertainty (0.015) on trend detection. Detection bias (top), percentage of missing detections (middle),  
 352 and percentage of false detections (bottom) were summarized for all statistically significant linear trends  
 353 for different actual NDVI trend levels.



354

355      Figure 4. Trends in Terra and Aqua MODIS NDVI over North America 2002-2010. Recent disturbances  
 356      from fire and wood harvest appear white, while water, cropland, and barren land cover types appear  
 357      black. Inset panels summarize statistically significant NDVI trends over land from each time series.